

Systems Science & Control Engineering

An Open Access Journal

ISSN: (Print) 2164-2583 (Online) Journal homepage: <http://www.tandfonline.com/loi/tssc20>

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To cite this article: Alhaji Shehu Grema & Yi Cao (2017) Receding horizon control for oil reservoir waterflooding process, Systems Science & Control Engineering, 5:1, 449-461, DOI: [10.1080/21642583.2017.1378935](https://doi.org/10.1080/21642583.2017.1378935)

To link to this article: <http://dx.doi.org/10.1080/21642583.2017.1378935>



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Published online: 02 Oct 2017.



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Receding horizon control for oil reservoir waterflooding process

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ABSTRACT

Waterflooding is a recovery technique where water is pumped into an oil reservoir for increase in production. Changing reservoir states will require different injection and production settings for optimal operation which can be formulated as a dynamic optimization problem. This could be solved through optimal control techniques which traditionally can only provide an open-loop solution. However, this solution is sensitive to uncertainties which is inevitable to reservoirs. Direct feedback control has been proposed recently for optimal waterflooding operations with the aim to counteract the effects of reservoir uncertainties. In this work, a feedback approach based on the principle of receding horizon control (RHC) was developed for waterflooding process optimization. Application of RHC strategy to counteract the effect of uncertainties has yielded gains that vary from 0.14% to 19.22% over the traditional open-loop approach. The gain increases with introduction of more uncertainties into the configuration. The losses incurred as a result of the effect of feedback is in the range of 0.25%–15.21% in comparison to 0.39%–31.51% for the case of traditional open-loop control approach.

ARTICLE HISTORY

Received 12 April 2017
Accepted 9 September 2017

KEYWORDS

Receding horizon; economic MPC; waterflooding; reservoir; optimal control; geological uncertainty

1. Introduction

The growing global population is associated with increase in energy demand and among various energy sources, oil is the top and remains the preferred fuel for transportation (ExxonMobil, 2014). Oil is naturally occurring hydrocarbon that is found beneath the earth surface in a structure called reservoirs. Reservoirs are porous which allow the oil to be stored and permeable that enable fluids transmission. Usually, new discovered oil reservoir is under intense pressure which is just sufficient to bring the oil to the surface and this phase of production is termed *primary recovery*. As production progresses, the reservoir pressure continues to fall and a point is eventually reached where production is supported by boosting the reservoir pressure through injection of fluids in *secondary and tertiary recovery phases*. When water is the injecting fluid, the process is called waterflooding (Grema, 2014).

Waterflooding process involves injection of water into the reservoir through injection well(s) which flushes the oil toward production well(s). It is the simplest and most economical means of production. However, reservoir properties are highly heterogeneous. Spatial variations of flow-determining properties result to non-uniform oil sweep. Therefore, waterflooding operation is faced with

problems of low sweep efficiency and premature water break-through.

The dynamics of reservoir require varying the rate of water injection with time for optimal oil production due to changing reservoir states. For this reason and the aforementioned problem, various studies were carried out in determining optimal injection and production settings for waterflooding operation where some performance indices such as recoveries and profitability are maximized (Brouwer & Jansen, 2004; Brouwer, Jansen, van der Starre, van Kruijsdijk, & Berentsen, 2001; Foss & Jensen, 2011; Grema & Cao, 2013; van Essen, Zandvliet, Van den Hof, Bosgra, & Jansen, 2009). Open-loop optimal control solutions as obtained by Brouwer and Jansen (2004) and Asadollahi and Naevdal (2009) relied on perfect reservoir models. However, it is almost impossible to obtain a perfect model of such complicated system because reservoir properties are highly uncertain. Even history-matched model which is usually used in oil industries to counteract uncertainties may fail to predict reality (Tavassoli, Carter, & King, 2004). There are other methods that exist in the literature for counteracting uncertainties. For instance, the use of reservoir realizations in robust optimization techniques has been reported in van Essen et al. (2009). This method assumes that the set of realizations capture

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all reservoir characteristics and production behaviour, and it is however, too conservative. Dynamic optimization method was also developed for batch processes called repeated learning algorithms. Unfortunately, reservoir production is not repeatable, hence the method is not applicable to waterflooding process (Grema & Cao, 2016).

Several authors are of the opinion that there should be a shift of paradigm to an efficient utilization of production measurements where control strategies are implemented in a closed-loop fashion (Brouwer, Naevdal, Jansen, Vefring, & van Kruijsdijk, 2004; Dilib & Jackson, 2013; Foss & Jensen, 2011; Jansen, Brouwer, & van Kruijsdijk, 2005; Sarma, Aziz, & Durlofsky, 2005). This led to studies on methodologies for automatic model updating (data assimilation) integrated with optimization of production systems in a closed-loop. The concept is receiving a great attention which is termed 'closed-loop reservoir management (CLRM)', 'real time reservoir management', 'self-learning reservoir management', 'e-fields' or 'smart field'. The key components of CLRM are model updating and optimization. Model upscaling/downscaling is also considered as an integral element of the system (Jansen et al., 2005). The aim is to increase reservoir performance using measurement and control techniques.

One of the earliest works to combine optimization with model updating in a closed-loop frame work is that of Aitokhuehi, Durlofsky, Artus, Yeten, and Aziz (2004). Optimal well type, location and trajectory were first optimized using genetic algorithms (GA). Optimization of valve settings was then performed using conjugate gradient algorithms (CG) with continuous model updating using probability perturbation method to maximize oil recovery. Several other works have reported the use of CLRM (Chen & Oliver, 2010; Chen, Oliver, & Zhang, 2009; Jansen et al., 2005; Naevdal, Brouwer, & Jansen, 2006; Overbeek, Brouwer, Naevdal, & Kruijsdijk, 2004; Sarma, Durlofsky, & Aziz, 2008; Sarma, Durlofsky, Aziz, & Chen, 2006; Wang, Li, & Reynolds, 2009).

A control algorithm was proposed to be included in multi-level structure of CLRM (van Essen, Van den Hof, & Jansen, 2013). In the work of Sarma (2006), the loop consists of a synthetic reservoir model representing the truth reservoir, a coarser reservoir model in time-step and space used for life-cycle optimization and a model predictive controller (MPC). A simple data-driven model developed with sub-space identification method was used for prediction in conjunction with the MPC.

In the work reported by Brouwer et al. (2004), performance of a closed-loop configuration was evaluated through two case studies where the methodology was compared to traditional and optimized (based on certain reservoir properties) approaches. Permeability was

the only uncertain property that was focused on. Almost same pattern of performance evaluation was followed by other researchers (Jansen et al., 2005; Naevdal et al., 2006; Overbeek et al., 2004; Sarma, 2006; Sarma et al., 2008; Wang et al., 2009) with uncertainty in either permeability or a combination of permeability and porosity. Comparison was basically made among the developed closed-loop method, a benchmark based on known geology, and an open-loop solution or a reactive control method.

The MPC configuration of van Essen et al. (2013) however, considered mismatches in permeability and grid refinement around the well. Similar to other work, the efficacy of the designed closed-loop was evaluated by comparing its performance to an open-loop based solution. In the work of Dilib and Jackson (2013), the robustness of their direct feedback relationship (formulated from a base model) was tested on more unexpected reservoir behaviours which include shape of relative permeability curves, horizontal permeability, width of shale-free zone and aquifer strength. Although more uncertainties were introduced in this work than the previous ones, the approach of performance evaluation is basically the same. It would be more helpful had the paper presented sensitivities of the feedback relationship to the various uncertainties.

A dynamic optimization method for waterflooding process was developed by Grema and Cao (2013) based on the principle of receding horizon control (RHC). Although, the dynamic approach was shown to have a superior performance over static optimization, no uncertainty was considered. In Grema and Cao (2016) and Grema, Landa, and Cao (2015), a dynamic feedback control solution based on principle of self-optimizing control was developed. The feedback control was found to be robust in the presence of several geological uncertainties.

Economic MPC (EMPC) has recently become a subject of interest among researchers. EMPC incorporates process optimization and control in which economic cost function is used directly in the MPC framework (Ellisa, Duranda, & Christofides, 2014). Ref. Sokoler et al. (2014) presented a Dantzig-Wolf decomposition algorithm for linear EMPC of dynamically decoupled subsystems. The algorithm was tested on an energy systems management case study. The objective function consists of an economic term (cost of operating the subsystems and the cost of violating soft output constraints) and a regularization term. In the work of Ma, Qin, and Salsbury (2014), an EMPC was developed for optimizing energy demand and cost for commercial building under system constraints. The EMPC was compared to the traditional control approach of preprogramming a temperature setpoint. An EMPC was designed using event-triggered approach to reduce computational burden. The

design considered both state feedback and output feedback cases (Zhang, Liu, & Liu, 2014). In the EMPC formulation of Jäschke, Yang, and Biegler (2014), sufficient conditions for nominal stability of economic nonlinear model predictive controller (ENMPC) was developed. A regularization term was calculated directly by deriving a constructive strategy so as to guarantee the incorporation of the regularization term to the economic cost function. Stability of ENMPC was also studied in Zanona, Grosb, and Diehl (2014). Ref. Touretzky and Baldea (2014) presented a combined scheduling and EMPC for control of buildings temperature. In the work, a dynamic scheduling problem was solved for a slow time scale, while in the fast time scale, a control scheme was designed with a short horizon which regulates the indoor temperature. A multiobjective MPC was developed by Maree and Imsland (2014) for optimal operation of cyclic processes. The methodology was applied to two case studies; acetylene hydrogenation and oil production from thin oil-rim reservoirs. Ref. Müllera, Angeli, and Allgöwera (2014) analysed the performance of EMPC with self-tuning terminal cost. A terminal region constraint was used in the solution of the optimization problem which led to performance improvement. An EMPC was designed using primal-dual formulation to minimize peak electricity demand of residential buildings by Colea, Morton, and Edgar (2014). In a related work by Mendoza-Serrano (2014), it was shown that the efficiency of EMPC in minimizing peak electricity demand will largely depend on the quality/accuracy of price and weather forecasts.

Although, uncertainties are inevitable in real systems, little attention has been given to its consideration in the context of EMPC. To counteract the effect of uncertainties using ENMPC, Luciaa, Andersson, Brandt, Diehlb, and Engell (2014) presented the use of multi-stage scenario-based NMPC. Uncertainties treatment through EMPC was also considered by Wang, Teichgraeber, Palazoglu, and El-Farra (2014) to minimize operating cost and environmental impact as well as to maximize revenue for a hybrid renewable energy system. They also showed that optimal power reference is affected by the length of the horizon selected. In fact, this is one aspect of ENPMC that receives very little attention. It is one of the objectives of this paper to explore different types of RHC and the effects of horizon length on the optimal performance of our proposed ENMPC.

In this work, dynamic optimization of reservoir waterflooding using the concept of RHC is reported. The paper is in two parts, the first part compared two forms of RHC which are fixed-end RHC (FERHC) and moving-end RHC (MERHC) with the assumption of perfect reservoir knowledge. The aim was to find the best RHC option that will be used in counteracting uncertainty. In the second part,

the developed feedback strategy was used to counter the effects of uncertainties in reservoir properties. These include uncertainties in permeability, porosity, geometry, size and structure. Here, three strategies were compared; an RHC approach, open-loop solutions (OC) based on a nominal model and a benchmark (BM) case which assumes perfect knowledge of the reservoir. The paper is arranged as follows: Problem formulation is given in Section 2 while Section 3 considered the approach for the study. Results and discussions are contained in Section 4 and then conclusion in Section 5.

2. Problem formulation

2.1. Reservoir dynamics

Reservoir models can be written in a discretized form as (Grema & Cao, 2016).

$$g(\mathbf{u}^k, \mathbf{x}^{k+1}, \mathbf{x}^k, \boldsymbol{\varphi}) = 0 \quad (1)$$

where \mathbf{u}^k and \mathbf{x}^k are a set of reservoir controls, and states vector respectively at time-step k , while $\boldsymbol{\varphi}$ is a vector of model parameters. The reservoir states and controls have influence on the outputs through measurement equations (Grema & Cao, 2016).

$$h(\mathbf{u}^k, \mathbf{x}^k, \mathbf{y}^k) = 0 \quad (2)$$

Reservoir states include saturations and pressure while control can be injection and production rates and/or well bottomhole pressures. Reservoir parameters can be combinations of permeabilities, porosities and transmissibilities. Measurements obtainable may include oil production rates, water production rates, and bottomhole pressures at different time periods.

2.2. Receding horizon control for waterflooding

The two forms of RHC strategies developed in this work are named FERHC and MERHC. The difference between the two is in scheduling of the prediction horizon. For FERHC as shown in Figure 1, the initial prediction period, T_p , is set to be equal to the total production time (divided

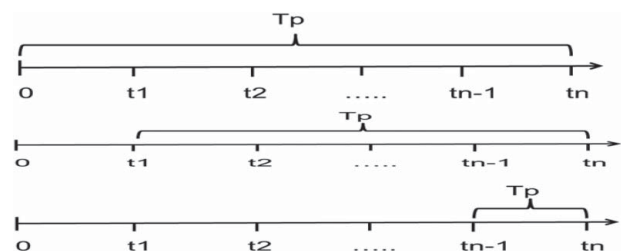


Figure 1. Fixed-end receding horizon.

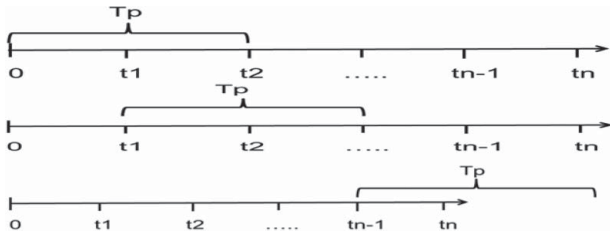


Figure 2. Moving-end receding horizon.

into n sampling periods) which then decreases subsequently by one sampling period as production advances. For MERHC on the other hand, the length of the prediction time remains constant but moves with production period, see Figure 2.

To counteract uncertainties in reservoir properties through RHC, two different reservoir models were used for the study; a prediction model to determine optimal well settings and implementation model where these well settings are implemented. The implementation model was assumed to be the real reservoir with uncertain properties that are different from those of the prediction model. The prediction model also served as a nominal model for determination of open-loop optimal control. A benchmark (BM) solution case was also developed with the assumption of a perfect reservoir model and properties known a priori.

The real reservoir provides synthetic measurements while the RHC reservoir was used to perform optimal control predictions. A physics-based reservoir model was used for the prediction in this work instead of data-driven model as is common with MPC for the simple reason that, data-driven models can never predict water breakthrough or saturations. They (data-driven models) can only predict pressures over a very short time for which saturations do not change appreciably (van Essen et al., 2013). Although, very time consuming, physics-based reservoir models provide more accurate predictions and better optimization performance over a long prediction horizon.

The methodology developed to counteract the effects of system/model mismatch is highlighted below:

- (1) Based on initial measurements from the real reservoir, initial states are chosen for the prediction model so that difference in real and predicted measurements is minimized.
- (2) An optimization is carried out with the adjusted initial states to determine control inputs for the starting step.
- (3) These optimal inputs u_{opt} are applied to both the RHC and real reservoir models where two sets of

measurements are obtained, predicted, Y_p and real, Y measurements respectively.

- (4) Output disturbance, d is taken as the difference between Y and Y_p which is added to Y_p for an update. The disturbance is assumed constant over the prediction horizon.
- (5) Optimization is carried out based on the updated measurements to obtain control inputs for the second time-step which are applied to both models.
- (6) Steps 3–5 above are repeated till the end of production time.

Figure 3 shows the flow chart for implementation of the above steps. A simplified diagram for such closed-loop system is given in Figure 4. Rate-controlled wells were considered.

The optimization in steps 2 and 5 is performed using optimal control theory (Brouwer et al., 2004).

2.3. Objective function

The objective is maximization of net present value (NPV) of the waterflooding process. NPV is the difference between the present values of the expected cash inflows and outflows over the production period. A positive NPV indicates a profitable venture while a negative one means the cost incurred outweighs the inflow. For the present work, water injection and production costs are the two sources of cash outflow while oil production represents revenue generation (Grema, 2014). NPV for a given sampling point, k is given as

$$J_k = \left\{ \frac{\sum_{j=1}^{N_{prod}} [r_o(y_{oj})_k - r_{wp}(y_{wj})_k] - \sum_{i=1}^{N_{inj}} r_{wi}(u_{wi})_k}{(1+b)^{(t_k/\tau)}} \right\} \Delta t \quad (3)$$

where N_{inj} and N_{prod} are number of injection and production wells, respectively, r_{wi} , r_{wp} and r_o are respective water injection and production costs, and oil price. u_w , y_w and y_o are water injection and production rates, and oil production rate, respectively. The discount factor is given as b , Δt is length of prediction horizon, t_k is the actual time period for which NPV is computed while τ is a reference time. In this work, b was set to 0% and 10%, r_{wi} and r_{wp} were each fixed at \$10/bbl while r_o was set to \$100/bbl (see Grema and Cao (2016)).

3. Approach

3.1. RHC for perfect reservoir model

Here, a perfect reservoir model was assumed, so there is no mismatch between the reservoir model used for

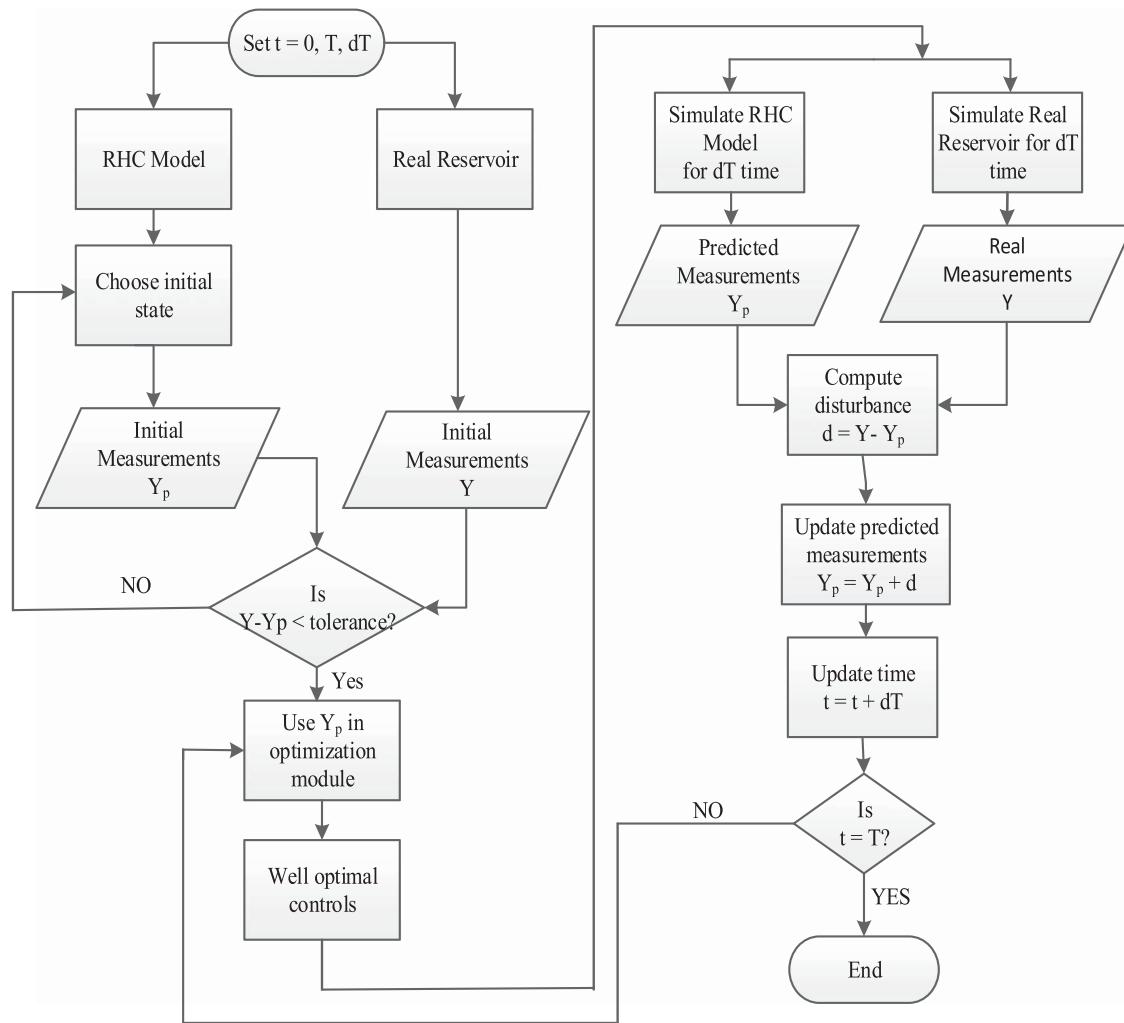


Figure 3. A flow chart for RHC strategy.

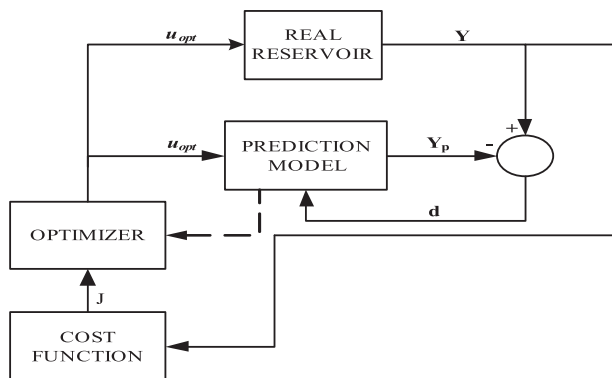


Figure 4. Receding horizon control loop.

control predictions and the actual reservoir for which the predicted controls are implemented. The aim is to first test the efficacy of the method through a comparative analysis with optimal control solutions; and secondly to compare the two RHC approaches in which a better option is chosen for uncertainty treatment.

Table 1. Rock and fluid properties.

Property	Value	Unit
Porosity	0.3	–
Oil viscosity	5	Cp
Water viscosity	1	Cp
Oil density	859	Kg/m ³
Water density	1014	Kg/m ³
Oil Corey exponent	2	–
Water Corey exponent	2	–

3.1.1. Reservoir and well configurations

The reservoir model was adopted from MRST package (SINTEF, 2014) and modified to suit our purpose. It has a size of 20 m × 20 m × 5 m. The reservoir has uniform permeability and porosity of 100 mD and 0.3 respectively. Only two-phase of incompressible oil and water was assumed to be flowing in the reservoir with properties given in Table 1. A vertical injection and a horizontal production wells were located arbitrarily as shown in Figure 5. The two wells are rate-controlled and an assumption of voidage replacement was made.

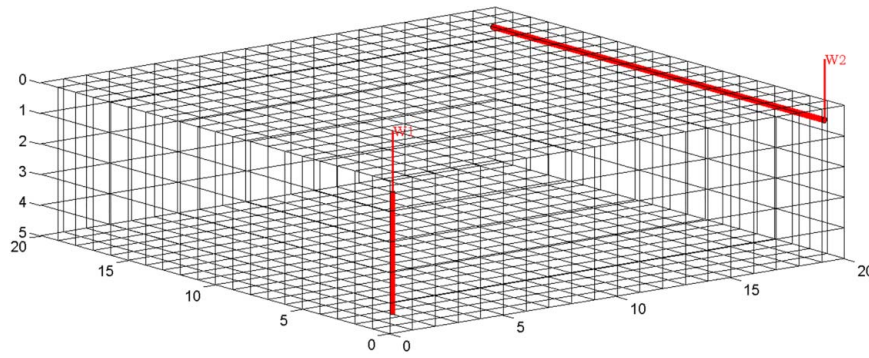


Figure 5. Reservoir and wells configuration for perfect modelled reservoir.

That is, total injection must equal total production at all time-steps.

3.1.2. Simulation procedure

Three optimization strategies were carried out and compared, an open-loop control solution, OC and two feedback strategies, FERHC and MERHC. Although, no reservoir uncertainty was considered, this methodology will give an idea of the relative performance of the two feedback methods and their deviations from the truth optimal solutions. The objective is maximization of NPV of the waterflooding process as given in (3).

The optimization procedures considered control of total production and injection rates for the two wells with an assumption of voidage replacement. That is, total injection must equal total production at all time-steps. A total of two years production period with two months (60 days) sampling period was used. So with this set up, for FERHC, optimization is initially performed for two years and the optimal rates found are implemented for two months. Then, the current reservoir state is used as an initial state for another 22-month optimization with the optimal rate applied for one sampling period. This process is continued for 20-, 18-, ... 2-month optimization and the corresponding optimal rates being implemented. For the case of MERHC, the prediction period is fixed. However, the length of this period will greatly influence the performance of the strategy. For this reason, different periods were tested and compared in this work. Typically, prediction periods of two, four, six and twelve months were compared. So, setting the prediction period to two months for example, optimal rates are predicted over this length of time and then implemented for one sampling period. The current reservoir state is used as a starting point for another two-month optimization with optimal rates implemented. The procedure is continued till the end of the optimization window.

3.2. RHC for uncertain reservoir model

3.2.1. Simulation procedure

FERHC (which was found to be better than MERHC) is applied here to deal with uncertainties in reservoir properties such as permeability, porosity and structure. Two different reservoir models were used for the study; a prediction model to determine optimal well settings and implementation model where these well settings are implemented. The implementation model was assumed to be the real reservoir with uncertain properties that are different from those of the prediction model. The prediction model also served as a nominal model for determination of open-loop optimal control. A benchmark (BM) solution case was also developed with assumption of a perfect reservoir model and properties known a priori.

The real reservoir provides synthetic measurements while the RHC reservoir was used to perform optimal control predictions. A physics-based reservoir model was used for the prediction in this work instead of data-driven model as is common with MPC for the simple reason that, data-driven models can never predict water breakthrough or saturations. They (data-driven models) can only predict pressures over a very short time for which saturations do not change appreciably (van Essen et al., 2013). Although, very time consuming, physics-based reservoir models provide more accurate predictions and better optimization performance over a long prediction horizon.

The measurements that are updated in step 3 of the RHC methodology discussed in Section 2.2 above are oil and water production rates given as

$$Y = [y_o \ y_w]^T \quad (4)$$

To evaluate the efficacy of this approach, its performance was compared against OC strategy where the optimal control inputs obtained based on the nominal reservoir model are implemented on the true reservoir model; and a benchmark case in which open-loop optimal controls were determined from the truth reservoir

model whose properties were assumed to be known a priori. For all approaches, NPV given in (3) was used as the objective function with economic parameters given in Section 2.3. Two simple indices were chosen for the comparative analyses:

- (1) The loss which is a deviation from the benchmark performance as a result of implementing either RHC or OC solution and computed from

$$Loss = \frac{J_{BM} - J_{RHC/OC}}{J_{BM}} \times 100\% \quad (5)$$

where J_{BM} is NPV obtained from the benchmark case and $J_{RHC/OC}$ the NPV obtained from either RHC or OC approach.

- (2) The gain which measures the benefit realizable through RHC implementation compared to OC given by

$$Gain = \frac{J_{RHC} - J_{OC}}{J_{RHC}} \times 100\% \quad (6)$$

It was found out that FERHC is better than MERHC for all cases (this will be presented in detail in Results and Discussion section). Based on this finding, it was then decided to adopt the former approach here to deal with uncertainties. A sampling time of one day was used for this analysis. Therefore, for a two-year production period, the initial prediction horizon is fixed to 730 days which then decreases subsequently by one day after every control implementation (see Figure 1). For the prediction of optimum well control, an adjoint formulation was applied for gradient computation (Brouwer et al., 2004).

3.2.2. Uncertainty consideration

Four different cases were considered. For the first case, uncertainty has not been introduced; both real and

prediction models are the same (nominal model was used). The reservoir used in Section 3.1 is adopted here as the nominal model which is a reservoir of size 20 m × 20 m × 5 m and homogenous in all fluid and rock properties. Specifically, the porosity and permeability are 0.3 and 100 mD respectively. However, both injection and production wells are vertical and are rate-constrained. As stated earlier, it is expected that RHC solution for this case would not be as good as open-loop optimal control due to the absence of model/system mismatch. However, the case would serve as a basis of comparison with other uncertainty cases.

In Case II, the prediction reservoir model differed from the real reservoir in permeability. All other properties of rocks, fluid, geometry and well configuration remain the same. The prediction reservoir model therefore, has a uniform permeability of 100 mD. The truth reservoir however, has five layers each with different permeability which is log-normally distributed with mean values of 200, 500, 350, 700, and 250 mD from top to bottom (Figure 6).

In addition to uncertainty in permeability, rock porosity was also assumed to be uncertain in Case III. The setup is the same as in Case II but the porosity of the truth reservoir and prediction model differs. Here, the nominal porosity remains at 0.3 while the real reservoir has a porosity of 0.45.

A lot of geological uncertainties were incorporated in Case IV which range from uncertainties in reservoir size, geometry and structure. The real reservoir was considered to be appreciably larger than the predictive reservoir whose size is 225 m × 22.5 m × 1 m. It was modelled with 30 × 3 × 1 cells using a corner point gridding system (predictive reservoir was modelled using a Cartesian grid). It also has a structural fault with width of 0.12 m. The fault can transmit fluids if the pressure drop across it is sufficient (Figure 7). Other rock and fluid properties are the same for both reservoirs.

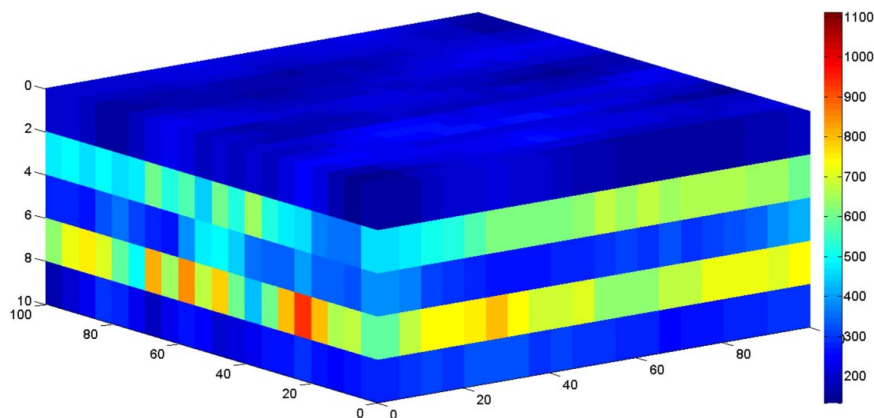


Figure 6. Permeability distribution for uncertain reservoir (Case II).

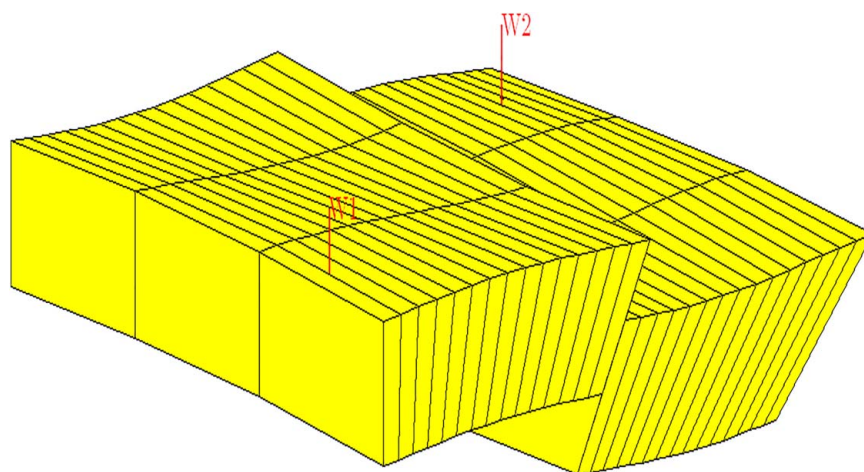


Figure 7. Uncertain reservoir with fault (Case IV).

4. Results and discussion

4.1. Optimization without uncertainty

A summary of the optimization results is given in Tables 2 and 3 for two cases of discount factor, b of 0% and 10% respectively. For the two cases, OC gave the highest NPV than the two RHC strategies due to the absence of model/system mismatch as expected. However, between the two feedback strategies, FERHC appears to be better than MERHC. In MERHC approach, effect of prediction horizon is well pronounced. For the case where $b = 0\%$, NPV increases with increase in prediction period with variation that has a standard deviation of \$2054 and a mean of \$140,990. Despite the fact that, OC generated the highest NPV, the difference is not significant. It is only 0.14% higher than FERHC and 1.88% in the case of MERHC (for $T_{pr} = 12$ months). The high NPV gain associated with OC can be attributed to a steady rise in water injection from the beginning of production to about 300 days which was maintained afterwards till the end of production time (Figure 8). This also corresponds to a similar rise in oil

Table 2. NPV for optimization strategies, discount factor = 0 (in 100,000 of \$).

OC	FERHC	MERHC			
		$T_{pr} = 2$ months	$T_{pr} = 4$ months	$T_{pr} = 6$ months	$T_{pr} = 12$ months
1.5920	1.5898	1.1115	1.4401	1.5259	1.5620

Table 3. NPV for optimization strategies, discount factor = 10% (in 100,000 of \$).

OC	FERHC	MERHC			
		$T_{pr} = 2$ months	$T_{pr} = 4$ months	$T_{pr} = 6$ months	$T_{pr} = 12$ months
1.5491	1.5386	1.1037	1.4246	1.5047	1.5272

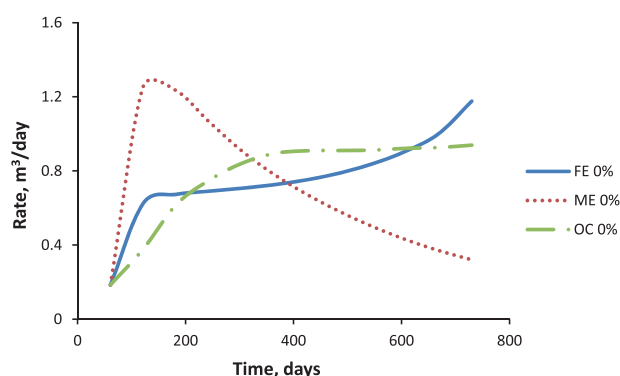


Figure 8. Water injection rates for different strategies ($b = 0\%$).

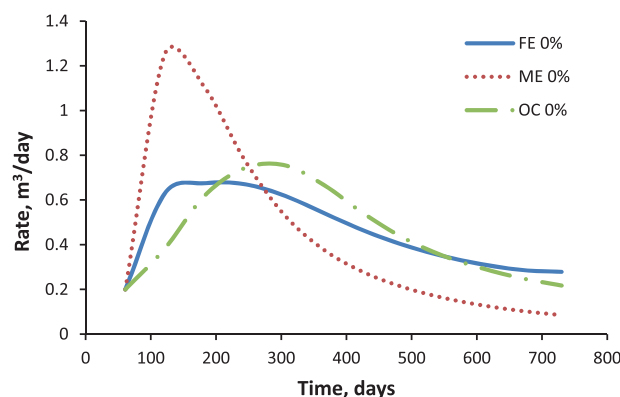


Figure 9. Oil production rates for different strategies ($b = 0\%$).

production as shown in Figure 9 with a more or less flattened plateau period and a delayed water production (Figure 10) which results to a higher total oil production (Figure 11).

A similar trend can be observed when $b = 10\%$. Here, variations in NPV with T_{pr} for MERHC strategy record a standard deviation of \$19,591 and a mean of \$139,010. The relative increases in NPV for the case of OC over

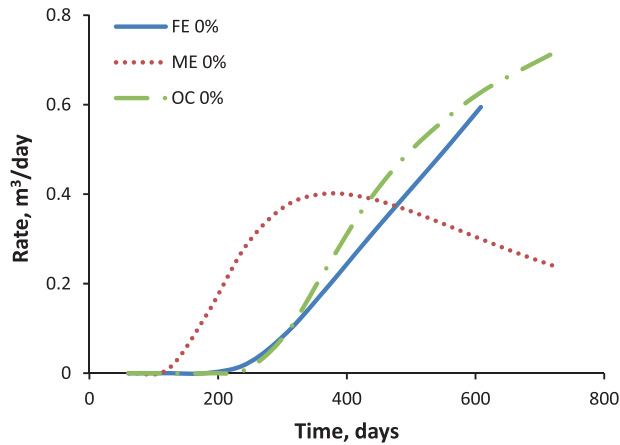


Figure 10. Water production rates for different strategies ($b = 0\%$).

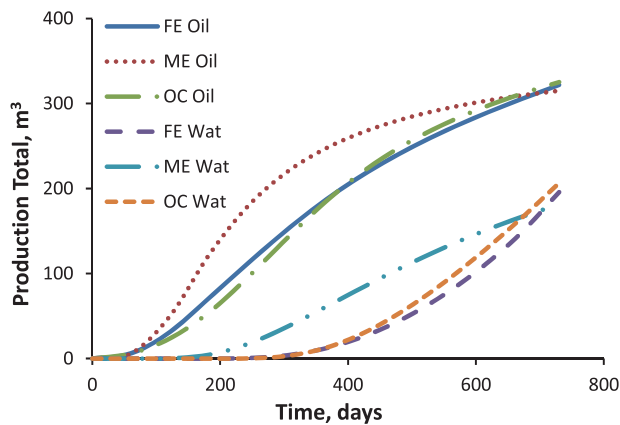


Figure 11. Total production for different strategies ($b = 0\%$).

Table 4. FERHC and OC comparison for Case I.

Strategy	Total oil (m ³)	Total water (m ³)	Time of water break-through (days)	NPV (\$)
FERHC	368.62	218.63	324	182,274.70
OC	370.69	215.91	317	182,775.04

FERHC and MERHC are 0.68% and 1.41% respectively (see Appendix).

4.2. Optimization under uncertainty

4.2.1. Case I: nominal reservoir properties

For the case where nominal parameter values were used (both real and prediction models are the same), NPVs for FERHC and OC approaches are respectively \$182,274.70 and \$182,775.04 which indicates a loss of only 0.27%. A brief summary of the results obtained is given in Table 4 where the similarity in the NPVs is further confirmed in the amount of total productions and water break-through time.

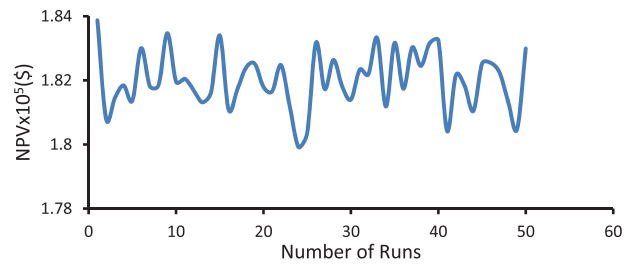


Figure 12. Sensitivity of NPV to permeability.

Table 5. Performance comparison – Case II.

Strategy	Total oil (m ³)	Total water (m ³)	Time of water break-through (days)	NPV (\$)
FERHC	336.91	249.33	186	159,320
OC	336.47	250.17	187	159,096
BM	344.28	280.33	142	159,724

4.2.2. Case II: uncertainty in reservoir permeability

Here, the prediction reservoir model has a uniform permeability of 100 mD while the truth reservoir has five layers with different permeability which is log-normally distributed with mean values of 200, 500, 350, 700, and 250 mD from top to bottom.

To investigate the extent to which error in the actual value of permeability can affect waterflooding performance, the sensitivity of the objective function, NPV to reservoir permeability was first studied. About 50 reservoir realizations were generated each with different permeability distributions. These realizations were simulated using open-loop optimal control obtained based on the nominal model.

It can be seen from Figure 12 that NPV is greatly affected by changes in permeability values. A minimum value in NPV of \$155,440.00 was obtained with a maximum value of \$159,700.00. The variation has a standard deviation of \$1141.20 and a mean of \$157,540.00. Hence, a feedback configuration such as RHC strategy can play a vital role in counteracting the effects of such modelling error. Table 5 summarizes the performance of the three approaches.

The use of FERHC in militating against the considered modelling error has incurred a loss in NPV of 0.25% as compared to 0.39% for the case of OC based on BM. Furthermore, the gain obtained in introducing feedback into the optimization process via FERHC is 0.14% over OC approach. The slight improvement obtained is due to a slight increase in oil production (0.13%) and a corresponding decrease in water production (0.34%) which is also evident from the difference in water break-through time (one day). Though the incremental change is not

Table 6. Performance comparison – Case III.

Strategy	Total oil (m ³)	Total water (m ³)	Time of water break-through (days)	NPV (\$)
FERHC	427.87	158.38	280	222,286.10
OC	425.70	160.93	274	220,918.20
BM	520.05	439.30	166	239,271.50

Table 7. Performance comparison – Case IV.

Strategy	Total oil (m ³)	Total water (m ³)	Time of water break-through (days)	NPV (\$)
FERHC	865.68	609.54	264	413,365.02
OC	587.73	0	–	333,904.67
BM	944.12	381.11	424	487,520.08

much, this perhaps is due to the size of reservoir considered and the prediction horizon used.

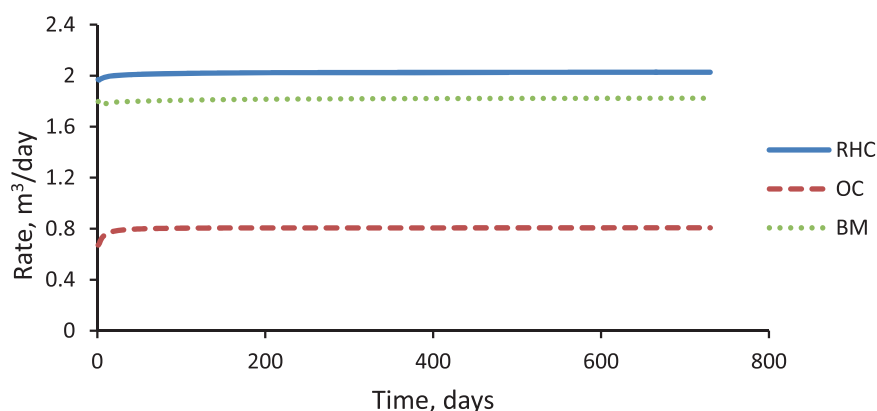
4.2.3. Case III: uncertainty in reservoir permeability and porosity

In addition to log-normal distribution in permeability in Case II, in this case the truth reservoir has a porosity of 0.45 as against 0.3 for the prediction model. With the increase in scale of uncertainty, the performance of FERHC has further improved in relation to OC. Here, the gain achieved is 0.67% as compared to 0.14% in Case II. A summary of performance is given in Table 6. However, the losses recorded have increased to 7.10% in the case of RHC and 7.67% for OC. The superior performance by FERHC strategy is attributed to a higher production in oil (0.67%) and lower water production (1.58%) (Table 6). A wide gap in productions is observed between the BM approach and the two strategies which translated to a corresponding gap in NPV. This wide difference was caused as a result of disparity between the total productions as shown in Table 6.

4.2.4. Case IV: uncertainty in reservoir size, geometry and structure

With the introduction of high degree of uncertainty in this case which includes uncertainties in reservoir size (real size of 225 m × 22.5 m × 1 m while nominal is 20 m × 20 m × 5 m), geometry (real geometry is corner point and Cartesian grid for the prediction model) and structure (presence of fault in the real reservoir), a very huge loss was incurred as a result of implementing an open-loop optimal solution with a value of 31.51%. However, the loss was drastically reduced by almost half through the use of measurements by FERHC (loss of 15.21%). The gain in this case is 19.22% in favour of FERHC. The open-loop NPV is not close in any way to the FERHC performance index which indicates a total failure of the former in the presence of these uncertainties.

Table 7 summarizes the obtained results where it can be seen that a reasonable amount of oil was produced via FERHC implementation which is comparable to the ideal amount (8.45% less), although the production was associated with high volume of water production; a reason that affected the NPV significantly. For the OC case however, a very low production was experienced. The zero-level water production is not a plus to this strategy; it is indeed an indication of inefficient reservoir sweeping. This can be further confirmed by observing the injection profiles of the three approaches in Figure 13. As it was shown, an average of 1.8 m³/day of water is required for an optimum flooding operation (BM), a requirement that has not been satisfied with an open-loop solution whose injection trajectory averages at 0.8 m³/day. In the case of FERHC, the optimum flooding requirement has been exceeded where the average injection rates throughout the production period is 2 m³/day. This is one of the reasons for the excessive water production which characterizes FERHC solution method for the considered reservoir system.

**Figure 13.** Injection rates for different strategies – Case IV.

5. Conclusions and recommendations

A feedback control approach based on receding horizon strategy was developed for optimization of reservoir waterflooding. The aim was to counteract uncertainties in reservoir properties while producing the reservoir optimally. The work was started with the development of two forms of RHC in which model/system mismatch was not considered. Based on the findings from this initial work, model/system mismatch was then introduced into the feedback configuration. The following conclusions were drawn:

- (1) For all considered cases, FERHC strategy performed better than MERHC.
- (2) The length of prediction horizon has an effect on the performance of MERHC approach. So, a considerable effort is needed to determine an optimum prediction period, which however, depends on the nature of the reservoir in question. As reservoir production is not repeatable, determination of optimum prediction period may not be realistic. Therefore, FERHC is preferable than MERHC for the case of waterflooding process.
- (3) The application of RHC strategy to counteract the effect of uncertainties has yielded gains that vary from 0.14% to 19.22% over the traditional open-loop approach. The gain increases with introduction of more uncertainties into the configuration. The losses incurred as a result of the effect of feedback is in the range of 0.25%–15.21% in comparison to 0.39%–31.51% for the case of OC approach.
- (4) Although, an improvement has been achieved by applying RHC strategies to annul the effect of model/system mismatch, it will be worth investigating other feedback approaches that may result to higher gains and less sensitive to uncertainties.

A fixed production period was used in this work, subsequent studies should investigate the use of the strategies with terminal conditions.

Acknowledgement

We are grateful to SINTEF Applied Mathematics for providing free licence of the software, MRST.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

The financial support of Petroleum Technology Development Fund (PTDF), Abuja is acknowledged.

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References

- Aitokhuehi, I., Durlofsky, L. J., Artus, V., Yeten, B., & Aziz, K. (2004). *Optimization of advanced well type and performance*. Presented at the 9th European conference on the mathematics of oil recovery (ECOMR IX), Cannes, France.
- Asadollahi, M., & Naevdal, G. (2009). *Waterflooding optimization using gradient based methods*. Presented at the SPE/EAGE reservoir characterization and simulation conference, Abu Dhabi, UAE.
- Brouwer, D. R., & Jansen, J. D. (2004). Dynamic optimization of waterflooding with smart wells using optimal control theory. *SPE JOURNAL*, 9(4), 391–402. doi:10.2118/78278-PA
- Brouwer, D. R., Jansen, J. D., van der Starre, S., van Kruijsdijk, C. P. J. W., & Berentsen, C. W. J. (2001). *Recovery increase through water flooding with smart well technology*. SPE European formation damage conference, The Hague, Netherlands.
- Brouwer, D. R., Naevdal, G., Jansen, J. D., Vefring, E. H., & van Kruijsdijk, C. P. J. W. (2004). *Improved reservoir management through optimal control and continuous model updating*. Presented at the SPE annual technical conference and exhibition, Society of Petroleum Engineers, Houston, TX.
- Chen, Y., & Oliver, D. S. (2010). Ensemble-based closed-loop optimization applied to brugge field. *SPE Reservoir Evaluation & Engineering*, 13, 56–71. doi:10.2118/118926-PA
- Chen, Y., Oliver, D. S., & Zhang, D. (2009). Efficient ensemble-based closed-loop production optimization. *SPE Journal*, 4, 634–645. doi:10.2118/112873-PA
- Colea, W. J., Morton, D. P., & Edgar, T. F. (2014). Optimal electricity rate structures for peak demand reduction using economic model predictive control. *Journal of Process Control*, 24(8), 1311–1317. doi:10.1016/j.jprocont.2014.04.014
- Dilib, F. A., & Jackson, M. D. (2013). Closed-loop feedback control for production optimization of intelligent wells under uncertainty. *SPE Production & Operation*, 28(04), 345–357.
- Ellisa, M., Duranda, H., & Christofides, P. D. (2014). A tutorial review of economic model predictive control methods. *Journal of Process Control*, 24(8), 1156–1178. doi:10.1016/j.jprocont.2014.03.010
- ExxonMobil. (2014). *The outlook for energy: A view to 2040*. Retrieved from <http://corporate.exxonmobil.com/en/energy/energy-outlook>
- Foss, B., & Jensen, J. P. (2011). Performance analysis for closed-loop reservoir management. *SPE Journal*, 16(1), 183–190. doi:10.2118/138891-PA
- Grema, A. S. (2014). *Optimization of reservoir waterflooding* (PhD.). Cranfield, Bedfordshire, UK, Cranfield University.
- Grema, A. S., & Cao, Y. (2013). *Optimization of petroleum reservoir waterflooding using receding horizon approach*. 8th IEEE conference on industrial electronics and applications, pp. 397–402, Melbourne, Australia.
- Grema, A. S., & Cao, Y. (2016). Optimal feedback control of oil reservoir waterflooding processes. *International Journal of Automation and Computing*, 13(1), 73–80. doi:10.1007/s11633-015-0909-7
- Grema, A. S., Landa, A. C., & Cao, Y. (2015). *Dynamic self-optimizing control for oil reservoir waterflooding*. Presented at the IFAC workshop on automatic control in offshore oil and gas production, vol. 48(6), pp. 50–55, Florianopolis, Brazil.

- Jansen, J.-D., Brouwer, D. R., & van Kruijsdijk, C. P. J. W. (2005). Closed-loop reservoir management. *First Break*, 23(1), 43–48.
- Jäschke, J., Yang, X., & Biegler, L. T. (2014). Fast economic model predictive control based on NLP-sensitivities. *Journal of Process Control*, 24(8), 1260–1272. doi:10.1016/j.jprocont.2014.04.009
- Luciaa, S., Andersson, J. A. E., Brandt, H., Diehl, M., & Engell, S. (2014). Handling uncertainty in economic nonlinear model predictive control: A comparative case study. *Journal of Process Control*, 24(8), 1247–1259. doi:10.1016/j.jprocont.2014.05.008
- Ma, J., Qin, S. J., & Salsbury, T. (2014). Application of economic MPC to the energy and demand minimization of a commercial building. *Timothy*, 24(8), 1282–1291.
- Maree, J. P., & Imsland, L. (2014). On multi-objective economic predictive control for cyclic process operation. *Journal of Process Control*, 24(8), 1328–1336. doi:10.1016/j.jprocont.2014.05.011
- Mendoza-Serrano, D. I. (2014). Smart grid coordination in building HVAC systems: EMPC and the impact of forecasting. *Journal of Process Control*, 24(8), 1301–1310. doi:10.1016/j.jprocont.2014.06.005
- Müllera, M. A., Angeli, D., & Allgöwera, F. (2014). On the performance of economic model predictive control with self-tuning terminal cost. *Journal of Process Control*, 24(8), 1179–1186. doi:10.1016/j.jprocont.2014.05.009
- Naevdal, G., Brouwer, D. R., & Jansen, J.-D. (2006). Waterflooding using closed-loop control. *Computational Geosciences*, 10, 37–60. doi:10.1007/s10596-005-9010-6
- Overbeek, K. M., Brouwer, D. R., Naevdal, G., & Kruijsdijk, C. P. J. W. (2004). *Closed-loop waterflooding*. Presented at the 9th European conference on the mathematics of oil recovery (ECOMOR IX), Cannes, France.
- Sarma, P. (2006). *Efficient closed-loop optimal control of petroleum reservoirs under uncertainty* (PhD.). Stanford University, USA.
- Sarma, P., Aziz, K., & Durlofsky, L. J. (2005). *Implementation of adjoint solution for optimal control of smart wells*. Presented at the SPE reservoir simulation symposium, Houston, Texas, USA.
- Sarma, P., Durlofsky, L. J., & Aziz, K. (2008). Computational techniques for closed-loop reservoir modeling with application to a realistic reservoir. *Petroleum Science and Technology*, 26(10–11), 1120–1140. doi:10.1080/10916460701829580
- Sarma, P., Durlofsky, L. J., Aziz, K., & Chen, C. (2006). Efficient real-time reservoir management using adjoint-based optimal control and model updating. *Computational Geosciences*, 10, 3–36. doi:10.1007/s10596-005-9000-z
- SINTEF. (2014). *MRST documentation page* (Online). Retrieved from <http://www.sintef.no/Projectweb/MRST/>
- Sokoler, L. E., Standardi, L., Edlund, K., Poulsen, N. K., Madsen, H., & Jørgensen, J. B. (2014). A dantzig–wolfe decomposition algorithm for linear economic model predictive control of dynamically decoupled subsystems. *Journal of Process Control*, 24(8), 1225–1236. doi:10.1016/j.jprocont.2014.05.013
- Tavassoli, M., Carter, J. N., & King, P. R. (2004). Errors in history matching. *SPE Journal*, 9(3), 352–361. doi:10.2118/86883-PA
- Touretzky, C. R., & Baldea, M. (2014). Integrating scheduling and control for economic MPC of buildings with energy storage. *Journal of Process Control*, 24(8), 1292–1300. doi:10.1016/j.jprocont.2014.04.015
- van Essen, G. M., Van den Hof, P., & Jansen, J.-D. (2013). A two-level strategy to realize life-cycle production optimization in an operational setting. *SPE Journal*, 18, 1057–1066. doi:10.2118/149736-PA
- van Essen, G., Zandvliet, M., Van den Hof, P., Bosgra, O., & Jansen, J.-D. (2009). Robust waterflooding optimization of multiple geological scenarios. *SPE Journal*, 14(01), 202–210.
- Wang, C., Li, G., & Reynolds, A. C. (2009). Production optimization in closed-loop reservoir management. *SPE Journal*, 506–523. doi:10.2118/109805-MS
- Wang, X., Teichgraber, H., Palazoglu, A., & El-Farra, N. H. (2014). An economic receding horizon optimization approach for energy management in the chlor-alkali process with hybrid renewable energy generation. *Journal of Process Control*, 24(8), 1318–1327. doi:10.1016/j.jprocont.2014.04.017
- Zanona, M., Grosb, S., & Diehl, M. (2014). Indefinite linear MPC and approximated economic MPC for nonlinear systems. *Journal of Process Control*, 24(8), 1273–1281. doi:10.1016/j.jprocont.2014.04.023
- Zhang, J., Liu, S., & Liu, J. (2014). Economic model predictive control with triggered evaluations: State and output feedback. *Journal of Process Control*, 24(8), 1197–1206. doi:10.1016/j.jprocont.2014.03.009

Appendix: Production profiles for reservoir without uncertainty and discount factor = 0

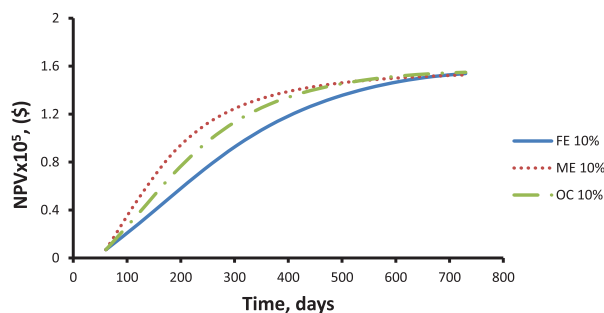


Figure A1. NPV for Different Strategies ($b = 10\%$).

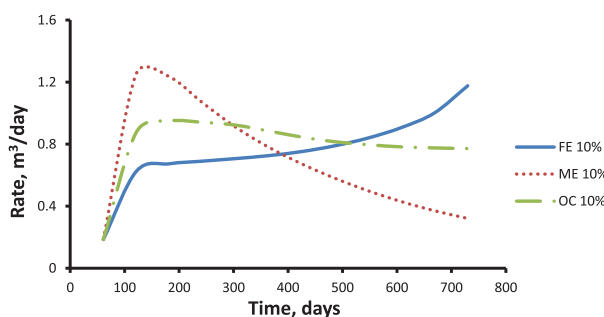


Figure A2. Water Injection Rates for Different Strategies ($b = 10\%$).

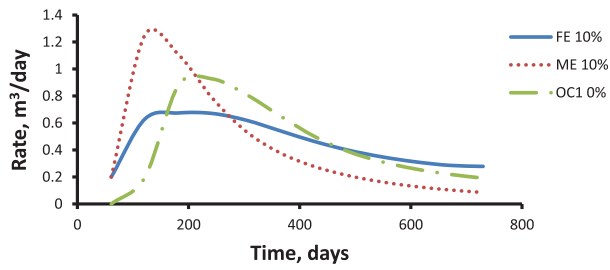


Figure A3. Oil Production Rates for Different Strategies ($b = 10\%$).

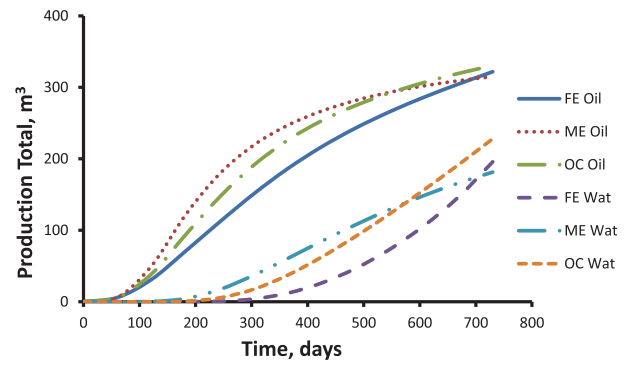


Figure A5. Total Production for Different Strategies ($b = 10$).

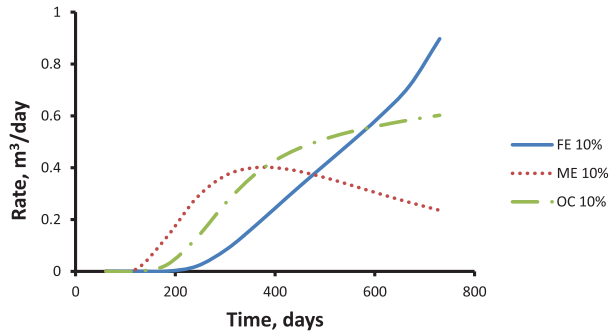


Figure A4. Water Production Rates for Different Strategies ($b = 10\%$).